US-PAT-NO: 5680481

DOCUMENT-IDENTIFIER: US 5680481 A

TITLE: Facial feature extraction method and apparatus for a neural network acoustic and visual speech recognition system

DATE-ISSUED: October 21, 1997

US-CL-CURRENT: 382/190, 382/118 , 382/159 , 382/193 , 382/202

APPL-NO: 08/ 488840

DATE FILED: June 9, 1995

PARENT-CASE:

This application is a continuation of application Ser. No. 08/130,287, filed Oct. 1, 1993 (now abandoned), which was a continuation-in-part of application Ser. No. 07/889,619, filed May 26, 1992, now U.S. Pat. No. 5,586,215.

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Brief Summary Text - BSTX (25):

A speech recognition system for recognizing utterances belonging to a preestablished set of allowable candidate

utterances comprises an acoustic
feature extraction apparatus, a dynamic visual
feature extraction apparatus,
and a neural network classifying apparatus. The
acoustic feature extraction
apparatus converts acoustic speech signals
representative of an utterance into
a corresponding spectral feature vector set. The
dynamic visual feature
extraction apparatus converts the dynamic **facial
features associated with the
generation** of the acoustic utterance into a dynamic
visual feature vector set.
The neural network classifying apparatus converts
the dynamic acoustic and
visual feature vectors into a conditional
probability distribution that
describes the **probability** of each candidate
utterance having been spoken given
the observed acoustic and visual data.

US-PAT-NO: 6556196

DOCUMENT-IDENTIFIER: US 6556196 B1

TITLE: Method and apparatus for the processing of images

DATE-ISSUED: April 29, 2003

US-CL-CURRENT: 345/419, 345/441 , 345/646 , 382/154

APPL-NO: 09/ 527158

DATE FILED: March 17, 2000

FOREIGN-APPL-PRIORITY-DATA:

COUNTRY	APPL-NO	APPL-DATE
EP	99105692	March 19, 1999

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Brief Summary Text - BSTX (10):
According to the invention, a parametric face modeling technique assists in solving both of the above problems. First, arbitrary human **faces can be created simultaneously controlling the likelihood of the generated faces**. Second, the system is able to compute correspondence between new faces. Exploiting the **statistics** of a large data set of 3D

face scans (geometric and textural data, Cyberware.TM.) a morphable face model has been built which allows to recover domain knowledge about face variations by applying pattern classification methods. The morphable face model is a multidimensional 3D morphing function that is based on the linear combination of a large number of 3D face scans. Computing the average face and the main modes of variation in the dataset, a **probability** distribution is imposed on the morphing function to avoid unlikely faces. Also, parametric descriptions of face attributes such as gender, distinctiveness, "hooked" noses or the weight of a person, have been derived by evaluating the distribution of exemplar faces for each attribute within our face space.

Detailed Description Text - DETX (3):

As illustrated in FIG. 1, starting from an example set of 3D face models, a morphable face model is derived by transforming the shape and texture of the examples into a vector space representation. The morphable face model contributes to two main steps in face manipulation: (1) deriving a 3D face model from a novel image, and (2) modifying shape and texture in a natural way. New **faces and expressions can be modeled by forming** linear combinations of the prototypes. Shape and texture constraints derived from the **statistics** of our example faces are used to guide manual modeling or automated matching algorithms. 3D face reconstructions from single

images and their applications for photo-realistic image manipulations can be obtained. Furthermore, face manipulations according to complex parameters such as gender, fullness of a face or its distinctiveness are demonstrated.

Detailed Description Text - DETX (14):

For a useful face synthesis system, it is important to be able to quantify the results in terms of their plausibility of being faces. We, therefore, estimated the **probability** distribution for the coefficients a.sub.i and b.sub.i from our example set of faces. This distribution enables us to control the likelihood of the coefficients a.sub.i and b.sub.i and quently regulates the likelihood of the appearance of the **generated faces**.

Detailed Description Text - DETX (69):

According to the invention a morphable face model has been built by automatically establishing correspondence between all of e.g. 200 exemplar faces. The interactive **face modeling system enables human users to create new characters and to modify facial** attributes by varying the model coefficients. The modifying facial attributes comprise e.g. gaining or loosing weight, frowning or smiling or even "being forced to smile". Within the constraints imposed by prior **probability**, there is a large variability of possible faces, and all linear combinations of the exemplar faces look natural.

US-PAT-NO: 5375195

DOCUMENT-IDENTIFIER: US 5375195 A

TITLE: Method and apparatus for generating composites of human faces

DATE-ISSUED: December 20, 1994

US-CL-CURRENT: 345/630

APPL-NO: 07/ 906101

DATE FILED: June 29, 1992

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Brief Summary Text - BSTX (20):
In the preferred embodiment, **generating a set of facial composites comprises randomly generating** the set after initially limiting the universe from which the set of **facial composites is generated** by sex, race, and other identifying characteristics. A set of unique strings of binary digits is randomly **generated, each of the strings corresponding to a unique facial** composite. Each of the composites is rated by a user on a scale of fitness to an observed human face (or any other desired face, such as a beautiful face). The rating may be performed or supplemented by measuring

physiological responses of a user. Combining the fittest facial composite and another facial composite comprises breeding two genotypes corresponding to the fittest **facial composite and another facial composite to generate an offspring genotype corresponding to the intermediate facial** composite. Breeding two genotypes comprises permitting crossover of genes between the two bred genotypes with a **probability** of 0.24 and mutation of genes within the two bred genotypes with a **probability** of 0.05.
The invention preferably further comprises permitting the user to prevent further changes to a specified feature of the intermediate composite and to modify a specified feature of the intermediate composite. The intermediate composite is placed in the set only if the fitness of the intermediate composite is greater than the fitness of a least fit facial composite of the set, in which case the least fit facial composite is removed from the set.

Detailed Description Text - DETX (43):

Flood Option: When subjects rated any generation of (20) composites, the highest rated composite from that generation was displayed in a window of the computer screen. Before breeding the next generation, subjects were now permitted to lock one or more features of this composite (hair, eyes, nose, mouth or chin). That section of the 35 bit string corresponding to the locked feature was then inserted into all the genotypes of that generation, before

breeding. Since all genotypes were then identical at the location of the locked feature, the cross-over operator could not modify that feature in the next **generation of faces**. (There is still a small **probability** of modification by mutation).

3. Relationship of fuzzy classifiers to statistical classifiers and neural classifiers

3.1 Fuzzy vs. Statistical

One of the most common questions regarding fuzzy set classification is how does it relate to statistical classification. What is the difference between the degree of membership (also known as possibility) in the set and the probability of being in that set? Once again refer to the fuzzy FAQ.

A good example that demonstrates the conceptual difference between statistical and fuzzy classification is the one given by Bezdek in the reference mentioned previously. In the example, a person who is dying of thirst in the desert is given two bottles of fluid. One bottle's label says that it has a 0.9 membership in the class of fluids known as non-poisonous drinking water. The other bottle's label states that it has a 90% probability of being pure drinking water and a 10% probability of being poison. Which bottle would you choose?

In the example, the "probability bottle" contains poison. This is quite plausible since there was a 1 in 10 chance of it being poisonous. The "fuzzy bottle" contains swamp water. This also makes sense since swamp water would have a 0.9 membership in the class of non-poisonous fluids. The point is that probability involves crisp set theory and does not allow for an element to be a partial member in a class. Probability is an indicator of the frequency or likelihood that an element is in a class. Fuzzy set theory deals with the similarity of an element to a class.

Both are valid approaches to the classification problem. If we were to classify someone as "old", fuzzy membership makes much more sense than probability. If we were to classify the outcome of a coin flip, probability makes much more sense.

3.2 Fuzzy vs. Neural

Both fuzzy systems and neural networks attempt to determine the transfer function between a feature space and a given class. (Note: if the reader is unfamiliar with neural networks, an excellent overview by Dr. Leslie Smith can be found here.) Both can be automatically adapted by the computer in an attempt to optimize their classification performance.

One difference between the two methods is that the membership functions of a fuzzy classifier can be initialized in a state close to the correct solution. What this means is that a fuzzy classifier can be set up by a skilled HCI designer to do a pretty good job of classification even before the classifier is adjusted by the computer. A neural network, however, can only be initialized in a random state. Thus, the training of the computer to optimize the classifier is usually much faster with a fuzzy classifier than a neural network classifier.

The problem with a fuzzy system is it is difficult to deal with too many features, membership functions, and/or rules. Neural networks, are highly suited for large amounts of features and classes.